

# PsyMo: A Dataset for Estimating Self-Reported Psychological Traits from Gait

Adrian Cosma  
 University Politehnica of Bucharest  
 Bucharest, Romania  
 cosma.i.adrian@gmail.com

Emilian Radoi  
 University Politehnica of Bucharest  
 Bucharest, Romania  
 emilian.radoi@upb.ro

## Abstract

*Psychological trait estimation from external factors such as movement and appearance is a challenging and long-standing problem in psychology, and is principally based on the psychological theory of embodiment. To date, attempts to tackle this problem have utilized private small-scale datasets with intrusive body-attached sensors. Potential applications of an automated system for psychological trait estimation include estimation of occupational fatigue and psychology, and marketing and advertisement. In this work, we propose PsyMo (Psychological traits from Motion), a novel, multi-purpose and multi-modal dataset for exploring psychological cues manifested in walking patterns. We gathered walking sequences from 312 subjects in 7 different walking variations and 6 camera angles. In conjunction with walking sequences, participants filled in 6 psychological questionnaires, totaling 17 psychometric attributes related to personality, self-esteem, fatigue, aggressiveness and mental health. We propose two evaluation protocols for psychological trait estimation. Alongside the estimation of self-reported psychological traits from gait, the dataset can be used as a drop-in replacement to benchmark methods for gait recognition. We anonymize all cues related to the identity of the subjects and publicly release only silhouettes, 2D / 3D human skeletons and 3D SMPL human meshes.*

## 1. Introduction

How we move and behave in the physical space is intrinsically tied to our psychological workings. Besides each individual's muscle developments and the influence of extrinsic factors, walking (or gait) is influenced by gender [10], emotions [4], personality traits [59], and mental distress [23]. Walking is an action performed ubiquitously by healthy individuals. So far, in the domain of AI-powered gait analysis, significant attention has been dedicated to gait recognition [2, 13, 17, 22, 28, 40, 69], but with little focus being dedicated to exploring the manifestations of psycholog-

ical traits in gait [29].

While there has been research in studying personality manifestations in video [11, 24, 43, 54], walking is left largely unexplored. Nonetheless, some studies [46, 59, 64] separately confirm significant differences in gait between individuals with different personalities, levels of aggression, depression and self-esteem. Such works are based on the assumption that psychological experience manifests itself into behaviour, in line with theories of embodiment [51, 74]. Embodiment suggests a biofeedback influence loop between the psyche and physical gestures / actions. Actions, gestures and posture can have a clear impact on thought [27], memory and recall [50], and mood [51, 53]. In this context, currently, there is no open dataset for exploring the embodied manifestation of psychological traits in gait.

We propose PsyMo (Psychological traits from Motion), a multi-purpose gait database containing 312 subjects walking under multiple viewpoints and walking variations, annotated with self-assessed psychological traits from 6 psychological questionnaires: Big Five Index [32], Rosenberg Self-Esteem [57], Buss-Perry Aggression [9], Occupational Fatigue Exhaustion/Recovery Scale [70], Depression Anxiety Stress Scale [45], and the General Health Questionnaire [26]. Across all subscales and factors, PsyMo contains 17 psychological traits. Alongside self-assessed psychological traits, participants also submitted their age, gender, height and weight. PsyMo is the first public dataset of its kind and pertains to the set of "controlled" gait datasets used for benchmarking gait analysis tasks under various walking variations, similar to CASIA-B [73] and FVG [75].

PsyMo covers 7 walking variations: normal walking, changing clothes, slow walking, fast walking, walking with a bag, and two additional dual-tasks (i.e. walking while performing a cognitive task [19]), largely ignored in current datasets: walking while texting and walking while talking on the phone. The walks are captured using 3 synchronized consumer video surveillance cameras (Tapo C200) to mimic adverse conditions (i.e. low-fps, fish-eye distortion, low-resolution) present in real-world surveillance scenarios, for

a total of 6 viewpoints (which include the round-trips). In total, we gathered 14,976 walking sequences.

We provide 2D / 3D human poses, silhouettes, and 3D human meshes for gait processing. We extracted appearance-based silhouettes using instance segmentation with a pretrained Hybrid Task Cascade (HTC) model [14], and 2D skeletons using AlphaPose [36], a state-of-the-art model for pose estimation. Further, we used CLIFF [39] to estimate 3D human pose and 3D meshes in the form of parametric SMPL predictions. The dataset is fully anonymized, and subjects gave explicit and informed consent for processing and distributing it. We do not release raw videos, as they can lead to identifying the subjects in our study. We release only processed gait information in the form of silhouettes, 2D / 3D skeletons and 3D human meshes.

PsyMo is primarily intended as a rich resource for exploring psychological manifestations into walking patterns, allowing for an interdisciplinary study into human behaviour from both the artificial intelligence and psychology research communities. We propose several evaluation procedures for the estimation of psychological traits from gait. Furthermore, due to its size and number of walking variations, PsyMo can also be used as a benchmark dataset for standard gait recognition, in addition to / as a more diverse drop-in replacement to existing gait benchmark datasets [60, 73, 75]. For this purpose, we also proposed several evaluation protocols for gait recognition.

## 2. Related Work

**Psychological Cues from Behaviour** There have been several attempts and datasets [33, 63] for personality detection from external body movement and nonverbal behaviour in literature. Subramanian et al. [63] proposed ASCERTAIN, a multimodal dataset for personality and affect recognition, in terms of Big Five personality traits. The dataset contains electroencephalogram (EEG), electrocardiogram (ECG), galvanic skin response (GSR) and facial activity readings for 58 subjects while viewing movie clips. The authors show that they can achieve above-chance recognition accuracy in emotional videos. This work provides evidence that personality affects physiological responses in the body. A large body of work is dedicated to *apparent personality*, based on human faces, body postures and behaviours [33]. Different from self-reported personality, apparent personality is based on external behavioural manifestations of a subject. In this area, numerous datasets are proposed, from multimodal (MHHRI [12], ChaLearn [21], SEMAINE [49]) to audiovisual (ELEA [58], Youtube Vlog [5–7]). Approaches generally make use of static face images [43], videos [11], audiovisual [24] cues and multimodal [54] features.

Regarding gait analysis, Satchell et al. [59] showed in a narrow study that there are statistically significant correla-

tions between gait features such as speed, cadence and limb range of motion and Big Five personality traits. Similarly, such correlations are found in terms of aggression (using the Buss-Perry Aggression scale). These findings motivate our work to explore automatic estimation of personality traits and signs of mental distress from walking in more realistic settings. Works in the area of depression detection and signs of mental distress from gait [23, 46, 72] generally make use of the PHQ-9 [34] for measuring depression or the GAD-7 [62] scale for measuring anxiety. However, the authors do not release the datasets to the research community. For instance, Fang et al. [23] extracted skeleton sequences of walking students using a Kinect sensor and computed several hand-crafted features for the gait data, such as walking speed, arm swing, stride length, and head movement. Using classical machine learning classifiers such as SVM and Random Forest, they obtained good results on depression detection. Sun et al. [64] obtained statistically significant correlations between self-esteem measured by the Rosenberg scale [57] and participants' gait. The authors collected a corpus of 178 graduate students to perform their experiments and estimated the individual skeletons using a Kinect sensor. Alongside cues for personality and mental distress cues, there are some works which tackle estimation of emotions from behaviour, and in particular gait [4, 15].

**Gait Analysis** Current works in gait analysis from video focus on identity recognition, regarding gait as a unique biometric fingerprint able to identify subjects [13, 18, 22, 73, 78]. Gait recognition is primarily performed on benchmark datasets [31, 71, 73, 75], collected in controlled scenarios, most prominently CASIA-B [73]. CASIA-B is one of the first medium-scale datasets used for training and evaluating the performance of models in various walking variations (normal walking, change in clothing, carrying conditions) and different viewpoints. It contains 126 subjects and 11 viewpoints. However, one limitation of CASIA-B is its lack of size, thus researchers tend to use it as a benchmark set, and train models on larger and more diverse sets such as GREW [78], Gait3D [76] or DenseGait [16]. Most current datasets are not annotated beyond subject identity, with only some providing annotations for age and gender [71]. FVG [75] is a similar controlled gait dataset, containing 226 individuals walking towards the camera. In addition to the walking variations present in CASIA-B, FVG also contains walking speed and the passage of time as confounding factors. GREW, Gait3D, and DenseGait are another class of gait databases, which are collected "in the wild", with no clear delimitation between walking variations. They represent a more challenging scenario for gait recognition, with orders of magnitude more identities and with real-world walking variations.

Approaches for gait analysis typically are classified

into appearance-based and model-based. Appearance-based methods more recently make use of silhouettes [13, 22, 28, 69] extracted either from background subtraction methods or from a pretrained instance segmentation model. Approaches typically use either a compressed form of the silhouette sequence through a Gait Energy Image (GEI) [28], or process the silhouettes as they are [13, 22]. Model-based approaches, on the other hand, make use of a model of the human body. More recently, such approaches entail the use of skeletons automatically extracted from pretrained pose estimation models [18], and processing them with architectures borrowed from skeleton action recognition, such as a CNN [17], an LSTM [2, 40] or graph methods such as ST-GCN [37, 38]. Furthermore, many recent works are starting to take advantage of the increasingly accurate predictions of the 3D human body model (e.g., SMPL [44]) and incorporate 3D information in their pipelines [60, 76, 77].

### 3. The PsyMo Dataset

To gather our dataset, we asked volunteers to fill in 7 psychological questionnaires and personal information about their body composition: age, gender, height and weight. After submitting the questionnaires, participants were required to have their walk captured in various conditions. All participants are physically healthy and do not report any injury or disability affecting their walking. Participants were dressed in everyday clothes. In total, 312 subjects participated in our study, mostly university students. All participants were explicitly informed about how their data is being processed and that the anonymized dataset is made available to the research community at large. Subsequently, all participants gave explicit consent to be part of this study before filling in the questionnaires. Moreover, this study was approved by the Ethics Review Board at the University Politehnica of Bucharest (AC01/01.10.2021). The dataset is made publicly available upon request, but reviewers can access it directly<sup>1</sup>. The dataset is protected by the CC-BY-NC-ND<sup>2</sup> License.

#### 3.1. Collecting Psychometric Data

As opposed to other similar works [23, 72], we have a more diverse set of questionnaires, which correspond to indicators of personality (BigFive, Rosenberg Self-Esteem), fatigue (OFER), aggressiveness (Buss-Perry Aggression Questionnaire) and mental health (General Health Questionnaire, Depression, Anxiety and Stress Scale). For the participants' convenience, we chose the short version of the questionnaires when possible, resulting in a total completion time of approximately 30 minutes for all questionnaires. Since all our subjects are native Romanians, we used

translations for each questionnaire when available. In case a translation is not available, we performed the translations with the help of a psychologist. Before capturing the walking videos, each participant was required to fill in the questionnaires. Of the 312 participants, 113 were female and 199 were male, with an average age of 21.9 years (SD = 2.18). The average weight for the participants is 70.5kg (SD = 15.7), with an average height of 174.8cm (SD = 8.9), corresponding to an average BMI of 22.87 (SD = 3.9). We briefly describe the motivation and technical details of each psychological questionnaire.

**Big Five Inventory (BFI)** The Big Five Inventory [32] is a widely used self-report scale for grouping personality traits. It is comprised of 44 items rated on a five-point Likert scale [68] from 1 ("disagree a lot") to 5 ("agree a lot"). Each item is a statement that is a verbal descriptor for a person's behaviour: "*I see myself as someone who ... is talkative / gets nervous easily / is reserved / tends to be lazy etc.*" Through factor analysis, the OCEAN (openness to experience, conscientiousness, extraversion, agreeableness, neuroticism) five factor model is revealed, describing the subject's personality. We chose the BFI as one of the questionnaires to explore the ways in which personality cues are present in human movement in the form of walking [55]. Previous works [59] have found strong correlations between big five personality and various aspects of gait (e.g. limb ranges of motion, gait speed). There are numerous applications of personality estimation from movement in real-life scenarios: marketing and advertisement, surveillance, pedestrian analysis and retail video analytics. BFI has been validated on the Romanian population [20], and we used one of the available Romanian translations. After completion, we obtain the following scores for the personality traits: Openness -  $M = 36.68$ ,  $SD = 5.37$ , Conscientiousness -  $M = 31.02$ ,  $SD = 5.81$ , Extraversion -  $M = 25.29$ ,  $SD = 5.48$ , Agreeableness -  $M = 33.45$ ,  $SD = 4.71$ , Neuroticism -  $M = 22.40$ ,  $SD = 5.59$ . BFI has no cutoff points for the final scores of each personality traits, but rather must be compared to a standard population. As such, we compute the score quantiles and for each personality trait (i.e. OCEAN) we obtain 4 ordinal classes: Low, Normal/Low, Normal/High and High.

**Rosenberg Self-Esteem (RSE)** Similar to the Big-Five Inventory, self-esteem is an important psychological trait, referring to the subjects' subjective evaluation of self-worth. Self-esteem is correlated with other psychological attributes: lower levels of self-esteem are associated with increased levels of depression and anxiety [67], and is strongly inversely correlated with neuroticism [1]. Nevertheless, we chose to collect a separate and explicit self-esteem score for more reliable estimation from gait and posture. Other works [64] report a significant correlation between some gait features and Rosenberg self-esteem scores.

<sup>1</sup>PsyMo Dataset Link: <https://bit.ly/3Q91ypD>

<sup>2</sup><https://creativecommons.org/licenses/by-nc-nd/4.0/legalcode>

The Rosenberg Self-Esteem Scale [57] contains 10 items that measure global self-worth, with both positive and negative attitudes towards the self. Each item is rated using a 4-point Likert scale from 0 ("strongly disagree") to 3 ("strongly agree"), with scores ranging from 0 to 30. The scale is validated on the Romanian population [56], and we use one of the available translations.

The Rosenberg Self-Esteem Scale is uni-dimensional, and after completion, we obtain an average score of 30.83 (SD = 5.50). Scores are recommended to be kept in a continuous scale [57], but for uniformity with the other questionnaires, we compute 3 ordinal classes (Low, Normal, High) using known thresholds.

**Buss-Perry Aggression Questionnaire (BPAQ)** The Buss-Perry Aggression Questionnaire [9] contains 29 items that measure physical aggression (9 items), verbal aggression (5 items), anger (8 items) and hostility (8 items). Items are scored using a 5 point Likert scale, ranging from 1 ("extremely uncharacteristic of me") to 5 ("extremely characteristic of me"). Works such as the one from Satchell et al. [59] found correlations between gait characteristics and factors of the BPAQ, indicating that automatic estimation is feasible. Estimating aggression from movement is crucial in safety situations by monitoring abnormal behaviour, i.e. in airports and train stations. After completion, we obtained the following scores for each factor: physical aggression - M = 24.65, SD = 3.71, verbal aggression - M = 11.55, SD = 3.51, anger M = 15.77, SD = 4.60, hostility - M = 17.83, SD = 4.52. Ordinal classes are obtained by quantization through quantiles. We obtain 4 classes: Low, Normal/Low, Normal/High and High.

**Occupational Fatigue Exhaustion/Recovery Scale (OFER)** Walking is a fundamental part of industrial workers in areas such as mining, construction and distribution centres. Manifestations of fatigue in walking are correlated with fatigue in other physical tasks and unintrusive estimation of workplace fatigue offers clear advantages for mitigation of workplace risks and monitoring of worker performance. To measure occupational fatigue, we used the Occupational Fatigue Exhaustion/Recovery Scale [70], which contains 15 items, split into 3 factors: chronic fatigue (5 items), acute fatigue (5 items) and recovery (5 items). It is mainly used as a psychometric indicator of inter-shift recovery rate and persistent occupational fatigue in the workplace. Each item in the OFER scale is scored using a 7-point Likert scale, ranging from 0 ("strongly disagree") to 6 ("strongly agree"). We translated each item with the help of a psychologist. Scores for each factor are calculated separately (item scores / 30 x 100), and the authors of the OFER questionnaire provide score thresholds for each factor. After completion, we obtain the following average scores: chronic fatigue - M = 38.08, SD = 21.30, acute fatigue - M = 40.20, SD = 19.42, recovery - M = 49.55, SD

= 17.7. As such, the final ordinal classes are divided into Low, Moderate/Low, Moderate/High and High.

**Depression, Anxiety and Stress Scale (DASS-21)** The Depression, Anxiety and Stress Scale [45] is a set of three self-report scales measuring depression, anxiety and stress, for a total of 42 items. DASS-21 is a widely accepted questionnaire and is suitable for clinical settings to assist in diagnosis, as well as non-clinical settings for screening mental health problems. The DASS scale measures signs of mental disorders, which could prove valuable if estimated from movement and gait in remotely monitoring the mental state of individuals in scenarios of assisted living, worker performance monitoring and healthcare institutions. Detection of mental health manifestations from movement is in line with the theory of embodiment [51], which suggests a reciprocal relationship between the psyche and movement. Similar to us, Fang et al. [23] constructed a system for depression detection from gait in Chinese university students, making use of PHQ-9 depression questionnaire [34], and obtained significant detection accuracy. However, we chose DASS-21 since it contains three subscales, including depression. Each item is rated on a 4-point Likert scale, ranging from 0 ("did not apply to me") to 3 ("applied to me very much, or most of the time"). It contains statements regarding negative emotional states that apply to an individual thinking about last week, before the moment of taking the inventory. In our work, we chose the short version with 21 items (DASS-21) for a faster completion time, without affecting the final scores. For each subscale, scores are in the range of 0 and 42. The authors provide translations in many languages, and we used the Romanian translation in our study. After completion, we obtained the following scores for each subscale: depression - M = 24.86, SD = 9.63, anxiety - M = 26.10, SD = 8.67, stress - M = 26.68, SD = 8.26. Ordinal classes for each subscale are computed based on the threshold values provided by the authors: Normal, Mild, Moderate, Severe and Extremely Severe.

#### General Health Questionnaire (GHQ)

The General Health Questionnaire [26] is a widely used scale for screening signs of mental distress and minor psychiatric disorders in the general population. The questionnaire is suitable for short term psychiatric disorders, but not long-standing mental health issues, and is usually regarded as a first step to inform further intervention. In our study, we used the short form (GHQ-12) for a faster completion time, with reliable results. The questionnaire is not scaled, and offers a single score to the individuals, assessing whether the subject's current mental state differs from "normal". Each of the 12 items is rated on a 4-point Likert scale, ranging from 0 ("not at all") to 3 ("more than usual"), with total scores ranging from 0 to 36. The scale is validated on the Romanian population [8], and we used an available translation for the Romanian language [8]. Similar to DASS-21,

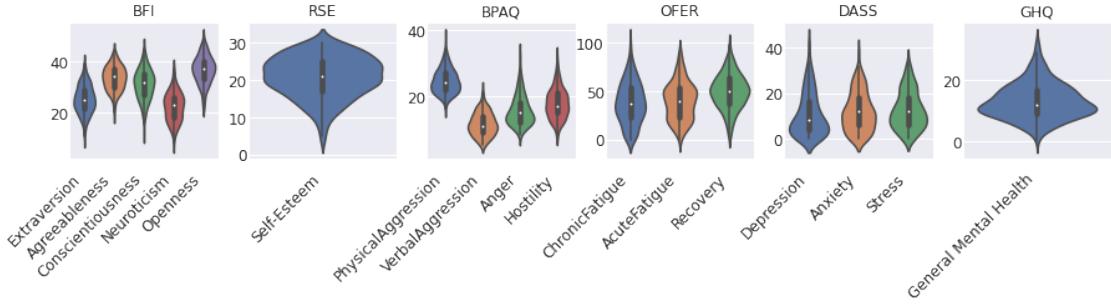


Figure 1. Violin plots for the distributions of questionnaire responses for all questionnaires and their corresponding factors / subscales.

GHQ-12 measures signs of mental health issues, with the same potential applications in real-world unintrusive estimation from movement. After completion, we obtained an average score of 13.27 (SD = 5.76). We used the available thresholds to obtain 3 ordinal classes: Typical, Minor Distress and Major Distress.

**Discussion** Figure 1 showcases the distribution of responses for each questionnaire and factors / subscales. While our population is mostly comprised of university students, there are no severe imbalances in the responses. Moreover, our questionnaire results are reliable and are validated by correlations found in psychology research. For instance, in our results, the Neuroticism factor in the Big Five Index is strongly correlated with other traits that we studied (Spearman's correlation  $p < 0.0001$ ), such as RSE, OFER and DASS scales. Neuroticism refers to a tendency to respond with negative emotion to unfavourable events such as frustration, loss and threat. Neurotic individuals are more likely to have lower self-esteem, are more tired and are more likely to experience signs of mental distress (depression, anxiety) [35]. Moreover, there are strong correlations between fatigue and anxiety / depression [61], also found in our dataset (Spearman's correlation  $p < 0.0001$ ). Self-esteem is inversely correlated with depression and anxiety [67], another property also found in our results (Spearman's correlation  $p < 0.0001$ ). Figure 2 showcases a heatmap of the correlation coefficients between each of the 17 traits in our dataset.

### 3.2. Capturing Walks

**Experimental Setup** Figure 4 showcases our gait capturing setup. Instead of capturing walks with a high-definition, high framerate camera, we opted for more realistic hardware to simulate real-world surveillance conditions. We chose three Tapo C200 consumer surveillance cameras, for their widespread availability, ease of use and ease of interaction via a web API. The cameras record video at 1920x1080 resolution, with a framerate of 16 frames per second and were positioned at  $0^\circ$ ,  $45^\circ$  and  $90^\circ$  angles from the walking area. The walking area is 8 meters long, which allows for

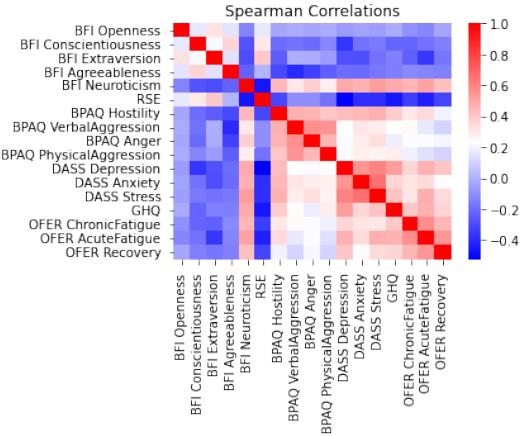


Figure 2. Spearman correlations between questionnaire scores.

5–6 full gait cycles [52], depending on the height of the person. In the laboratory there was only one researcher present alongside the subject at any given time, to avoid influencing the subject's walking. Friesen et al. [25] showed a positive correlation between the number of researchers present in the laboratory and changes in gait speed and cadence, while not being affected by the participants' personalities.

In Figure 3 we show all the walking variations and viewpoints. Alongside the standard array of covariates [47, 73, 75] which includes normal walking (NM), changing clothing (CL), carry bag (CB) and walking speed (in our case walking speed slow - WSS and walking speed fast - WSF), we also introduce two covariates that are often ignored in the literature, but nevertheless appear frequently in the wild, dual-tasks, which have been shown to produce walking variability in adults [19]. We introduce walking while texting (TXT) and walking while talking on the phone (PH). In total, our dataset contains 7 walking variations. For each variation, participants were asked to walk a round-trip, in a comfortable manner. For the normal walking variation, participants walked two round-trips. As such, there are a total of 48 walking sequences per participant,



Figure 3. Walking variations and viewpoints for the gait sequences in our dataset. Participants walked in 7 variations (NM, CL, BG, WSS, WSF, TXT and PH) and their walks were captured from 6 viewpoints.

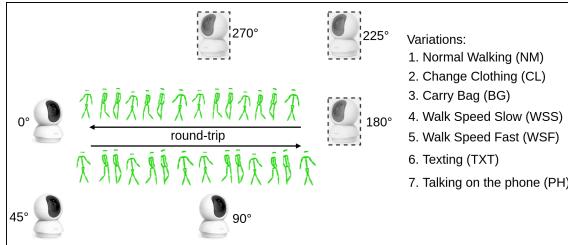


Figure 4. Setup for capturing walking sequences. We employed three synchronized Tapo C200 consumer cameras, at three angles:  $0^\circ$ ,  $45^\circ$  and  $90^\circ$ . Since subjects perform a round-trip, we have an additional 3 virtual angles of  $180^\circ$ ,  $225^\circ$  and  $270^\circ$ . Subjects walk a total of 16 times across variations, corresponding to 48 walks from all viewpoints and variations.

from 7 variations and 6 viewpoints ( $3 \times 4$  NM +  $3 \times 2 \times 6$  other variations).

**Data Processing** In order to preserve the anonymity of the participants, we do not release the full RGB videos, and instead choose to release only high-level features related to gait: silhouettes, 2D / 3D human poses and 3D human meshes (Figure 5). We chose state-of-the-art pretrained models that have especially good performance in “in the wild” scenarios, which are arguably more complex than our laboratory conditions: more people, filmed at a distance, with detection overlap. As such, we make a reasonable assumption that the resulting semantic data (skeletons / silhouettes) is of high quality. However, we are committed to maintaining the dataset’s quality, and we intend to update the semantic features with improved models over time, if necessary. We extracted silhouettes using a pretrained Hybrid Task Cascade (HTC) [14] model, with a ResNet50 [30] backbone, trained on MSCOCO [42]. Silhouettes are widely used as an input representation for appearance-based gait analysis [3, 13, 22, 28, 41, 69]. After processing the videos, silhouettes are centred in the image and downsampled

to 128x128 pixels. Furthermore, for convenience, we computed a Gait Energy Image (GEI) [28] for each walk.

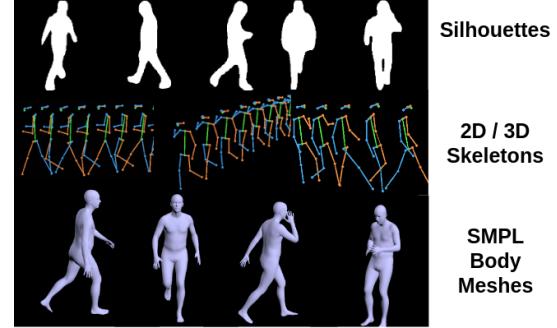


Figure 5. We publicly release only processed silhouettes, 2D / 3D skeleton sequences and 3D human meshes / SMPL. Raw RGB videos are not made available to protect the privacy of the subjects in our study.

Skeleton sequences are also used in modern, model-based approaches for gait analysis [2, 17, 37, 38, 40]. Currently, methods using skeletons sequences are outperformed by silhouette-based methods, since the extraction quality severely affects downstream computation. It is not clear whether silhouette-based methods are processing gait strictly in the form of movement, or also rely on the limited appearance information contained by the silhouette. However, skeletons allow for a more low-level analysis of walking patterns by analyzing the movement and correlation between the joints and individual body parts. We extracted 2D skeletons using AlphaPose [36], a state of the art, multi-person 2D pose estimation model. AlphaPose extracts skeletons in the COCO pose format, consisting of 18 joints, with (x, y) coordinates in the image space and a confidence score for each joint, which roughly measures the detection quality. We do not do any further processing on the poses and release them as is, in JSON format.

Further, many gait analysis works are increasingly using 3D human meshes in their processing pipeline to aid recognition and disambiguate 2D signals [60, 76, 77]. We extracted 3D human poses and triangle meshes (in the form of SMPL [44] models) using CLIFF [39], a global context-aware model, that has shown good results in 3D mesh extraction in the wild. For each walking video, we release the 3D pose (24 joints with x, y, z coordinates, centred at the pelvis) and SMPL parameters (10-dimensional vector) without any further modification.

### 3.3. Evaluation Protocols

In all protocols, subjects with IDs from 0-250 should be used for training, and evaluation ought to be performed on subjects with IDs from 251-312, corresponding to an 80:20 training-evaluation split.

**Psychological Traits Estimation** For psychological traits estimation on PsyMo, we propose two evaluation methodologies: (i) *run-level* and (ii) *subject-level*. For *run-level* evaluation, the model performance is evaluated for each walking sequence, irrespective of the subject. Performance in terms of precision, recall, weighted  $F_1$  score should be reported for all combinations of walking variations and viewpoints. This protocol is similar to a typical gait classification task (i.e. input walking sequence, output classes). For *subject-level* evaluation, the goal is to correctly identify the psychometric attributes for each subject, considering all available variations or runs. For instance, a naive baseline for subject-level evaluation is to use the run-level model and report the majority predicted classes for a questionnaire for all the runs of a subject. Methods for subject-level evaluation may consider the identity of the subject to be known at test time - a scenario possible in the real-world, as a part of a larger pipeline for gait recognition and classification. The same metrics as in run-level evaluation should be used.

**Gait Recognition** Larger “in the wild” datasets such as GREW and Gait3D are typically not annotated with information on walking covariates, and instead focus on benchmarking models’ ability to scale to many identities. While these datasets are more realistic from both hardware and environment perspectives, it is hard to quantify failure cases accurately (e.g. model fails on a particular walking variation). Smaller, more controlled datasets such as CASIA-B and FVG have a smaller number of identities, but with a fixed number of covariates. PsyMo brings together the best of both worlds by replicating real-world video hardware for capturing walks and annotating each run with more variations and with metadata information about each subject (gender, age, weight, height). In Table 1, we showcase a comparison of PsyMo to other popular datasets for the gait recognition task. As such, PsyMo can be used as an additional benchmark and drop-in replacement of older datasets (e.g., CASIA-B [73], de facto standard) for evaluating gait

recognition models.

Since PsyMo is by design similar in collection and variations with CASIA-B [73], we propose the same evaluation procedures: performing for each variation  $6 \times 6 = 36$  experiments, for each viewpoint. In each experiment, the gallery set is comprised of only the second NM run, while the probe set is comprised of all other variations and viewpoints, excluding the viewpoint present in the gallery. This protocol evaluates the model’s robustness to changes in viewpoints and walking variations.

## 4. Baseline Results

We provide baseline results for psychological trait estimation for the three data modalities present in this dataset. In Table 2, we present the weighted  $F_1$  score averaged across all walking variations and viewpoints. For 2D skeletons, we used GaitFormer [16], a skeleton transformer model used in gait recognition, and GaitGraph [66], a graph-based skeleton model. Further, for silhouettes, we used GaitSet [13] and GaitGL [41], two models achieving state-of-the-art results for gait recognition. Finally, for SMPL body meshes, we trained SMPLGait [76], a model combining both silhouettes and SMPL parameters to spatially transform the silhouettes according to the camera angle. We train a separate model for each factor / subscale using a standard weighted cross-entropy loss. Each model is trained three times, and the results are averaged. For *subject-level* evaluation, we make predictions for every run of an identity and the final prediction is the majority vote across runs.

Preliminary baseline results show that some psychological factors, such as mental distress and fatigue are more easily discernible from silhouettes than from skeletons. SMPLGait [76], which incorporates SMPL parameters and silhouette sequences into the model, fairs reasonably well in run-level evaluation compared to other silhouette methods, but does not seem to have a substantial improvement in subject-level. This implies that the predictions are not consistent across the different walks of the same person. GaitFormer [16], the only transformer-based architecture that considers a whole skeleton as a token, has substantial improvements in subject-level evaluation, outperforming the majority of other models across modalities.

Naturally, the *subject-level* evaluation protocol yields significantly higher results, prompting the future use of a more general class of models that can process sets of runs in an end-to-end fashion. PsyMo is a challenging dataset, and encourages the development of novel architectures that are better able to estimate psychological traits from sets of walking sequences. Moreover, future works might exploit the multi-modal nature of PsyMo, as well as the natural correlations between questionnaire subscales and employ a multi-modal / multi-task approach.

Table 1. Comparison of popular datasets for gait recognition. PsyMo is similar in size and variations to other datasets, but is annotated with gender, height, weight and psychological attributes for each subject. GREW [78], Gait3D [76] and DenseGait [16] are collected in the wild and have no clear delimitation between variations and viewpoints.

Dataset	Type	# IDs	# Seq.	Variations	Views	Env.	Demogr.	BMI	Particularity
FVG [75]	Controlled	226	2,857	NM, CL, BG, WS, CBG	3	Outdoor	$\times$	$\times$	time difference
CASIA-B [73]	Controlled	124	13,640	NM, CL, BG	11	Indoor	$\times$	$\times$	–
OU-ISIR [48]	Controlled	10,307	144,298	–	14	Indoor	$\checkmark$	$\times$	treadmill
Gait3D [76]	In the Wild	4,000	25,309	–	–	Indoor	$\times$	$\times$	collected in a supermarket
GREW [78]	In the Wild	26,000	128,000	–	–	Outdoor	$\checkmark$	$\times$	–
DenseGait [16]	In the Wild	217,954	217,954	–	–	Outdoor	$\times$	$\times$	auto labelled with 42 attributes
PsyMo (ours)	Controlled	312	14,976	NM, CL, BG, WSS, WSF, TXT, PH	6	Indoor	$\checkmark$	$\checkmark$	17 psychological traits

Table 2. Baseline results for each of the three modalities. Results presented are weighted F1 scores, averaged across variations / viewpoints. We present both run-level and subject-level results (i.e. identity-based majority voting).

	Method	Modality	BFI (4-classes)				RSE (3-classes)			BPAQ (4-classes)			OFER (4-classes)			DASS (5-classes)			GHQ (3-classes)	
			O	C	E	A	N	Esteem	Phys.	Verbal	Anger	Host.	Chronic	Acute	Recov.	Depr.	Anxiety	Stress	GHQ	
Run-Level	GaitFormer [16]	2D Skeletons	23.80	25.35	<b>27.88</b>	<b>28.12</b>	28.21	43.59	28.27	<b>31.89</b>	<b>31.24</b>	28.84	27.43	33.05	34.83	28.27	24.55	43.69	49.38	
	GaitGraph [66]	2D Skeletons	22.10	24.89	26.39	26.09	23.67	45.49	27.86	24.21	24.24	27.83	25.17	29.61	30.82	19.45	42.73	52.94		
	GaitSet [13]	Silhouettes	26.60	<b>26.51</b>	25.81	26.87	27.89	45.40	26.51	29.93	27.71	28.81	<b>31.13</b>	33.14	34.80	42.20	<b>27.57</b>	<b>51.98</b>	<b>56.11</b>	
	GaitGL [41]	Silhouettes	<b>26.64</b>	23.48	25.70	25.94	28.30	44.73	26.28	29.99	28.16	27.90	30.35	31.92	32.95	37.64	25.03	46.03	54.79	
	SMPLGait [76]	Silhouettes + SMPL	24.14	20.83	23.21	25.75	<b>32.21</b>	<b>45.90</b>	<b>28.32</b>	28.09	24.13	<b>30.18</b>	30.07	<b>34.54</b>	<b>35.05</b>	<b>42.74</b>	21.91	51.67	52.22	
Subject-Level	GaitFormer [16]	2D Skeletons	<b>33.12</b>	31.03	<b>36.27</b>	<b>38.42</b>	33.25	<b>55.58</b>	<b>38.00</b>	<b>42.81</b>	<b>42.73</b>	<b>39.09</b>	<b>36.71</b>	<b>38.88</b>	<b>46.80</b>	38.45	<b>36.33</b>	52.85	57.21	
	GaitGraph [66]	2D Skeletons	24.40	28.91	27.55	31.33	27.55	50.95	34.81	23.76	26.51	32.37	28.19	28.30	35.88	19.94	48.01	53.10		
	GaitSet [13]	Silhouettes	27.50	<b>31.55</b>	26.55	27.13	27.37	48.38	32.37	36.46	30.94	30.87	32.99	33.13	36.70	<b>46.64</b>	33.53	55.05	<b>60.59</b>	
	GaitGL [41]	Silhouettes	31.04	23.78	28.05	23.15	30.73	48.35	26.89	41.79	30.37	28.80	34.22	36.96	37.31	46.20	27.75	<b>55.57</b>	60.54	
	SMPLGait [76]	Silhouettes + SMPL	22.77	18.02	19.74	26.80	<b>36.51</b>	48.62	33.80	33.42	20.47	34.89	31.83	37.27	38.71	42.66	21.89	52.72	58.97	

## 5. Limitations and Societal Broader Impact

While we strive to make PsyMo realistic from a surveillance hardware standpoint (i.e. commercial cameras, 16 fps, HD resolution), the researcher’s presence in the laboratory might affect the manner of walking of the subject. Takayanagi et al. [65] found a weak positive correlation between the number of researchers present in the indoor laboratory and the gait speed of subjects. However, this correlation is significantly weaker when only one researcher is present. Our dataset contains mostly students of similar age, all of whom are from Romania, which makes the dataset biased in this age group, culture and upbringing. As such, the intended usage of PsyMo is to pave the way for exploratory methods into psychological traits present in movement, in the form of walking, and to develop narrow models in this domain. It is not meant to be a benchmark generalizable across all age groups, cultures and races. The recommended approach for this dataset is fine-tuning on PsyMo general-purpose models pretrained on diverse datasets such as GREW [78] or DenseGait [16]. In terms of the potential negative societal impact, we acknowledge that gait analysis can be used for intrusive surveillance practices, and advances in gait analysis may allow bad actors to profile and target individuals without their consent. However, PsyMo is intended only for research purposes and only enables the possibility for interdisciplinary studies of psychological manifestations into gait.

## 6. Conclusions

We proposed PsyMo, a dataset containing 14,976 walking sequences captured with commodity video surveillance hardware and annotated with 17 self-reported psychological attributes. It contains 312 subjects walking in different 6 viewpoints and 7 variations, including two actions-while-walking / dual-task variations (texting and talking on the phone). The dataset is anonymized, and we release only processed silhouettes extracted by an HTC model [14], skeleton sequences extracted with AlphaPose [36], and SMPL body meshes extracted with CLIFF [39]. Additional data modalities and updated representations with improved models will be added over time, if necessary. The purpose of PsyMo is to encourage interdisciplinary research into automatic estimation of psychological traits in biomechanical movement. The dataset is challenging and it encourages the development of novel, higher-level architectures that are able to take advantage of multiple walking sequences at the same time. The natural correlations between psychological subscales can be exploited in a multi-task fashion. Due to its size and diversity, PsyMo can also be used to benchmark methods for gait recognition as a drop-in replacement or alongside other popular gait datasets.

## Acknowledgements

This work was partly supported by CRC research grant 2021, with funds from UEFISCDI in project CORNET (PN-III 1/2018) and by the Google IoT/Wearables Student Grants. We thank Diana Todea for her psychology insights, and Andy Catrună, Laura Ruse and Dan Tudose for their help with the dataset collection.

## References

[1] Fatemeh Amirazodi and Maryam Amirazodi. Personality traits and self-esteem. *Procedia-Social and Behavioral Sciences*, 29:713–716, 2011. 3

[2] Weizhi An, Rijun Liao, Shiqi Yu, Yongzhen Huang, and Pong Chi Yuen. Improving gait recognition with 3d pose estimation. In *CCBR*, 2018. 1, 3, 6

[3] Khalid Bashir, Tao Xiang, and Shaogang Gong. Gait recognition using gait entropy image. In *3rd International Conference on Imaging for Crime Detection and Prevention (ICDP 2009)*, pages 1–6, 2009. 6

[4] Uttaran Bhattacharya, Christian Roncal, Trisha Mittal, Rohan Chandra, Kyra Kapsakis, Kurt Gray, Aniket Bera, and Dinesh Manocha. Take an emotion walk: Perceiving emotions from gaits using hierarchical attention pooling and affective mapping. In *European Conference on Computer Vision*, pages 145–163. Springer, 2020. 1, 2

[5] Joan-Isaac Biel and Daniel Gatica-Perez. Vlogcast yourself: Nonverbal behavior and attention in social media. In *International Conference on Multimodal Interfaces and the Workshop on Machine Learning for Multimodal Interaction*, pages 1–4, 2010. 2

[6] Joan-Isaac Biel and Daniel Gatica-Perez. Voices of vlogging. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 4, pages 211–214, 2010. 2

[7] Joan-Isaac Biel and Daniel Gatica-Perez. The youtube lens: Crowdsourced personality impressions and audiovisual analysis of vlogs. *IEEE Transactions on Multimedia*, 15(1):41–55, 2012. 2

[8] Andreea Brabete, María Sánchez-López, and Raquel Rivas. Ghq-12 in romanian people: reliability, exploratory and confirmatory factor analysis. 09 2012. 4

[9] Arnold H Buss and Mark Perry. The aggression questionnaire. *Journal of personality and social psychology*, 63(3):452, 1992. 1, 4

[10] Andy Catruna, Adrian Cosma, and Ion Emilian Radoi. From face to gait: Weakly-supervised learning of gender information from walking patterns. In *2021 16th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2021)*, pages 1–5. IEEE, 2021. 1

[11] Oya Celiktutan and Hatice Gunes. Computational analysis of human-robot interactions through first-person vision: Personality and interaction experience. In *2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 815–820. IEEE, 2015. 1, 2

[12] Oya Celiktutan, Efstratios Skordos, and Hatice Gunes. Multimodal human-human-robot interactions (mhhri) dataset for studying personality and engagement. *IEEE Transactions on Affective Computing*, 10(4):484–497, 2017. 2

[13] Hanqing Chao, Yiwei He, Junping Zhang, and Jianfeng Feng. Gaitset: Regarding gait as a set for cross-view gait recognition. In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, pages 8126–8133, 2019. 1, 2, 3, 6, 7, 8

[14] Kai Chen, Jiangmiao Pang, Jiaqi Wang, Yu Xiong, Xiaoxiao Li, Shuyang Sun, Wansen Feng, Ziwei Liu, Jianping Shi, Wanli Ouyang, et al. Hybrid task cascade for instance segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4974–4983, 2019. 2, 6, 8

[15] Mangtik Chiu, Jiayu Shu, and Pan Hui. Emotion recognition through gait on mobile devices. In *2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, pages 800–805. IEEE, 2018. 2

[16] Adrian Cosma and Emilian Radoi. Learning gait representations with noisy multi-task learning. *Sensors*, 22(18), 2022. 2, 7, 8

[17] Adrian Cosma and Ion Emilian Radoi. Multi - task learning of confounding factors in pose-based gait recognition. In *2020 19th RoEduNet Conference: Networking in Education and Research (RoEduNet)*, pages 1–6, 2020. 1, 3, 6

[18] Adrian Cosma and Ion Emilian Radoi. Wildgait: Learning gait representations from raw surveillance streams. *Sensors*, 21(24):8387, 2021. 2, 3

[19] Omar Costilla-Reyes, Patricia Scully, Iracema Leroi, and Krikor B. Ozanyan. Age-related differences in healthy adults walking patterns under a cognitive task with deep neural networks. *IEEE Sensors Journal*, 21(2):2353–2363, 2021. 1, 5

[20] Daniel David, Dragoș Iliescu, Silviu Matu, and Robert Balaszi. The national psychological/personality profile of romanians: An in depth analysis of the regional national psychological/personality profile of romanians. *Romanian Journal of Psychology*, 17(2), 2015. 3

[21] Hugo Jair Escalante, Isabelle Guyon, Sergio Escalera, Julio Jacques, Meysam Madadi, Xavier Baró, Stephane Ayache, Evelyne Viegas, Yağmur Güçlütürk, Umut Güçlü, et al. Design of an explainable machine learning challenge for video interviews. In *2017 International Joint Conference on Neural Networks (IJCNN)*, pages 3688–3695. IEEE, 2017. 2

[22] Chao Fan, Yunjie Peng, Chunshui Cao, Xu Liu, Saihui Hou, Jiannan Chi, Yongzhen Huang, Qing Li, and Zhiqiang He. Gaitpart: Temporal part-based model for gait recognition. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 14225–14233, 2020. 1, 2, 3, 6

[23] Jing Fang, Tao Wang, Cancheng Li, Xiping Hu, Edith Ngai, Boon-Chong Seet, Jun Cheng, Yi Guo, and Xin Jiang. Depression prevalence in postgraduate students and its association with gait abnormality. *IEEE Access*, 7:174425–174437, 2019. 1, 2, 3, 4

[24] Sheng Fang, Catherine Achard, and Séverine Dubuisson. Personality classification and behaviour interpretation: An approach based on feature categories. In *Proceedings of the 18th ACM International Conference on Multimodal Interaction*, pages 225–232, 2016. 1, 2

[25] Kenzie B. Friesen, Zhaotong Zhang, Patrick G. Monaghan, Gretchen D. Oliver, and Jaimie A. Roper. All eyes on you: how researcher presence changes the way you walk. *Scientific reports*, 10(1):17159–17159, Oct 2020. 33051502[pmid]. 5

[26] David P Goldberg and Barry Blackwell. Psychiatric illness in general practice: a detailed study using a new method of case identification. *Br med J*, 2(5707):439–443, 1970. 1, 4

[27] Susan Goldin-Meadow and Sian L Beilock. Action’s influence on thought: The case of gesture. *Perspect Psychol Sci*, 5(6):664–674, Nov. 2010. 1

[28] Ju Han and Bir Bhanu. “individual recognition using gait energy image”. *IEEE transactions on pattern analysis and machine intelligence*, 28:316–22, 03 2006. 1, 3, 6

[29] Elsa J. Harris, I-Hung Khoo, and Emel Demircan. A survey of human gait-based artificial intelligence applications. *Frontiers in Robotics and AI*, 8, 2022. 1

[30] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016. 6

[31] Martin Hofmann, Jürgen Geiger, Sebastian Bachmann, Björn Schuller, and Gerhard Rigoll. The tum gait from audio, image and depth (gaid) database: Multimodal recognition of subjects and traits. *Journal of Visual Communication and Image Representation*, 25(1):195–206, 2014. 2

[32] Oliver P John, Sanjay Srivastava, et al. The big five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and research*, 2(1999):102–138, 1999. 1, 3

[33] Julio Cezar Silveira Jacques Junior, Yağmur GüçlüTÜRK, Marc Pérez, Umut Güçlü, Carlos Andujar, Xavier Baró, Hugo Jair Escalante, Isabelle Guyon, Marcel AJ Van Gerven, Rob Van Lier, et al. First impressions: A survey on vision-based apparent personality trait analysis. *IEEE Transactions on Affective Computing*, 2019. 2

[34] K Kroenke, R L Spitzer, and J B Williams. The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med*, 16(9):606–613, Sept. 2001. 2, 4

[35] Benjamin B. Lahey. Public health significance of neuroticism. *The American psychologist*, 64(4):241–256, 2009. 19449983[pmid]. 5

[36] Jiefeng Li, Can Wang, Hao Zhu, Yihuan Mao, Hao-Shu Fang, and Cewu Lu. Crowdpose: Efficient crowded scenes pose estimation and a new benchmark. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10863–10872, 2019. 2, 6, 8

[37] Na Li and Xinbo Zhao. A strong and robust skeleton-based gait recognition method with gait periodicity priors. *IEEE Transactions on Multimedia*, pages 1–1, 2022. 3, 6

[38] Na Li, Xinbo Zhao, and Chong Ma. Jointsgait: A model-based gait recognition method based on gait graph convolutional networks and joints relationship pyramid mapping. *arXiv e-prints*, pages arXiv–2005, 2020. 3, 6

[39] Zhihao Li, Jianzhuang Liu, Zhensong Zhang, Songcen Xu, and Youliang Yan. Cliff: Carrying location information in full frames into human pose and shape estimation. In *Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part V*, pages 590–606. Springer, 2022. 2, 7, 8

[40] Rijun Liao, Chunshui Cao, Edel B. Garcia, Shiqi Yu, and Yongzhen Huang. Pose-based temporal-spatial network (ptsn) for gait recognition with carrying and clothing variations. In Jie Zhou, Yunhong Wang, Zhenan Sun, Yong Xu, Linlin Shen, Jianjiang Feng, Shiguang Shan, Yu Qiao, Zhenhua Guo, and Shiqi Yu, editors, *Biometric Recognition*, pages 474–483, Cham, 2017. Springer International Publishing. 1, 3, 6

[41] Beibei Lin, Shunli Zhang, and Xin Yu. Gait recognition via effective global-local feature representation and local temporal aggregation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 14648–14656, 2021. 6, 7, 8

[42] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014. 6

[43] Leqi Liu, Daniel Preotiuc-Pietro, Zahra Riahi Samani, Mohsen E Moghaddam, and Lyle Ungar. Analyzing personality through social media profile picture choice. In *Tenth international AAAI conference on web and social media*, 2016. 1, 2

[44] Matthew Loper, Naureen Mahmood, Javier Romero, Gerard Pons-Moll, and Michael J Black. Smpl: A skinned multi-person linear model. *ACM transactions on graphics (TOG)*, 34(6):1–16, 2015. 3, 7

[45] Sydney H Lovibond and Peter F Lovibond. *Manual for the Depression Anxiety Stress Scales, second ed.* Sydney: Psychology Foundation, 1995. 1, 4

[46] Haifeng Lu, Wei Shao, Edith Ngai, Xiping Hu, and Bin Hu. A new skeletal representation based on gait for depression detection. In *2020 IEEE International Conference on E-health Networking, Application & Services (HEALTHCOM)*, pages 1–6, 2021. 1, 2

[47] Y. Makihara, H. Mannami, A. Tsuji, M.A. Hossain, K. Suguri, A. Mori, and Y. Yagi. The ou-isir gait database comprising the treadmill dataset. *IPSJ Trans. on Computer Vision and Applications*, 4:53–62, Apr. 2012. 5

[48] Y. Makihara, H. Mannami, A. Tsuji, M.A. Hossain, K. Suguri, A. Mori, and Y. Yagi. The ou-isir gait database comprising the treadmill dataset. *IPSJ Trans. on Computer Vision and Applications*, 4:53–62, Apr. 2012. 8

[49] Gary McKeown, Michel Valstar, Roddy Cowie, Maja Pantic, and Marc Schroder. The semaine database: Annotated multimodal records of emotionally colored conversations between a person and a limited agent. *IEEE transactions on affective computing*, 3(1):5–17, 2011. 2

[50] Johannes Michalak, Katharina Rohde, and Nikolaus F Troje. How we walk affects what we remember: gait modifications through biofeedback change negative affective memory bias. *J Behav Ther Exp Psychiatry*, 46:121–125, Sept. 2014. 1

[51] Johannes Michalak, Nikolaus F Troje, Julia Fischer, Patrick Vollmar, Thomas Heidenreich, and Dietmar Schulte. Embodiment of sadness and depression—gait patterns associated with dysphoric mood. *Psychosomatic medicine*, 71(5):580–587, 2009. 1, 4

[52] M. Pat Murray, A. Bernard Drought, and Ross C. Kory. Walking patterns of normal men. *JBJS*, 46(2), 1964. 5

[53] Erik Peper, I-Mei Lin, Richard Harvey, and Jacob Perez. How posture affects memory recall and mood. *Biofeedback*, 45:36–41, 04 2017. 1

[54] Faezeh Rahbar, Salvatore M Anzalone, Giovanna Varni, Elisabetta Zibetti, Serena Ivaldi, and Mohamed Chetouani. Predicting extraversion from non-verbal features during a face-to-face human-robot interaction. In *International Conference on Social Robotics*, pages 543–553. Springer, 2015. 1, 2

[55] Michael D. Robinson, Adam K. Fetterman, Brian P. Meier, Michelle R. Persich, and Micheal R. Waters. *Embodied Perspectives on Personality*, pages 477–498. Springer International Publishing, Cham, 2021. 3

[56] Viorel Robu, Anișoara Sandovici, and Lavinia Maria Pruteanu. Scala rosenberg pentru evaluarea stimei de sine: Uni-sau multidimensionalitate? rezultate ale unui studiu psihometric în populația de adolescenți. *Revista de psihologie*, 2015. 4

[57] Morris Rosenberg. *Society and the Adolescent Self-Image*. Princeton University Press, 2015. 1, 2, 4

[58] Dairazalia Sanchez-Cortes, Oya Aran, Marianne Schmid Mast, and Daniel Gatica-Perez. A nonverbal behavior approach to identify emergent leaders in small groups. *IEEE Transactions on Multimedia*, 14(3):816–832, 2011. 2

[59] Liam Satchell, Paul Morris, Chris Mills, Liam O'Reilly, Paul Marshman, and Lucy Akehurst. Evidence of big five and aggressive personalities in gait biomechanics. *Journal of non-verbal behavior*, 41(1):35–44, 2017. 28203036[pmid]. 1, 2, 3, 4

[60] Mauricio Pamplona Segundo, Cole Hill, and Sudeep Sarkar. Long range gait matching using 3d body fitting with gait-specific motion constraints. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 603–612, 2023. 2, 3, 7

[61] María-José Serrano-Fernández, Joan Boada-Grau, María Boada-Cuerva, and Andreu Vigil-Colet. Work addiction as a predictor of anxiety and depression. *Work*, (Preprint):1–10, 2021. 5

[62] Robert L Spitzer, Kurt Kroenke, Janet B W Williams, and Bernd Löwe. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arch Intern Med*, 166(10):1092–1097, May 2006. 2

[63] Ramanathan Subramanian, Julia Wache, Mojtaba Khomami Abadi, Radu L. Vieriu, Stefan Winkler, and Nicu Sebe. Ascertain: Emotion and personality recognition using commercial sensors. *IEEE Transactions on Affective Computing*, 9(2):147–160, 2018. 2

[64] Bingli Sun, Zhan Zhang, Xingyun Liu, Bin Hu, and Ting-shao Zhu. Self-esteem recognition based on gait pattern using kinect. *Gait Posture*, 58:428–432, Sept. 2017. 1, 2, 3

[65] Naoto Takayanagi, Motoki Sudo, Yukari Yamashiro, Sang-yoon Lee, Yoshiyuki Kobayashi, Yoshifumi Niki, and Hiroyuki Shimada. Relationship between daily and in-laboratory gait speed among healthy community-dwelling older adults. *Scientific reports*, 9(1):1–6, 2019. 8

[66] Torben Teepe, Ali Khan, Johannes Gilg, Fabian Herzog, Stefan Hörmann, and Gerhard Rigoll. Gaitgraph: Graph convolutional network for skeleton-based gait recognition. In *2021 IEEE International Conference on Image Processing (ICIP)*, pages 2314–2318. IEEE, 2021. 7, 8

[67] Lonneke A van Tuijl, Peter J de Jong, B Esther Sportel, Eva de Hullu, and Maaike H Nauta. Implicit and explicit self-esteem and their reciprocal relationship with symptoms of depression and social anxiety: A longitudinal study in adolescents. *Journal of behavior therapy and experimental psychiatry*, 45(1):113–121, 2014. 3, 5

[68] W Paul Vogt and Burke Johnson. *Dictionary of statistics & methodology: A nontechnical guide for the social sciences*. Sage, 2011. 3

[69] Chen Wang, Junping Zhang, Jian Pu, Xiaoru Yuan, and Liang Wang. Chrono-gait image: A novel temporal template for gait recognition. In Kostas Daniilidis, Petros Maragos, and Nikos Paragios, editors, *Computer Vision – ECCV 2010*, pages 257–270, Berlin, Heidelberg, 2010. Springer Berlin Heidelberg. 1, 3, 6

[70] PC Winwood, AH Winefield, D Dawson, and K Lushington. Development and validation of a scale to measure work-related fatigue and recovery: the occupational fatigue exhaustion/recovery scale (ofer). *Journal of Occupational and Environmental Medicine*, pages 594–606, 2005. 1, 4

[71] Chi Xu, Yasushi Makihara, Gakuto Ogi, Xiang Li, Yasushi Yagi, and Jianfeng Lu. The ou-isir gait database comprising the large population dataset with age and performance evaluation of age estimation. *IPSJ Trans. on Computer Vision and Applications*, 9(24):1–14, 2017. 2

[72] Jingjing Yang, Haifeng Lu, Chengming Li, Xiping Hu, and Bin Hu. Data augmentation for depression detection using skeleton-based gait information. *Medical & Biological Engineering & Computing*, 60(9):2665–2679, 2022. 2, 3

[73] Shiqi Yu, Daoliang Tan, and Tieniu Tan. A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition. In *18th International Conference on Pattern Recognition (ICPR'06)*, volume 4, pages 441–444. IEEE, 2006. 1, 2, 5, 7, 8

[74] Alberto Zatti and Cristina Zarbo. Embodied and exbodied mind in clinical psychology. a proposal for a psycho-social interpretation of mental disorders. *Frontiers in Psychology*, 6:236, 2015. 1

[75] Ziyuan Zhang, Luan Tran, Feng Liu, and Xiaoming Liu. On learning disentangled representations for gait recognition. In *IEEE Transactions on Pattern Analysis and Machine Intelligence, Sep. 2019*, June 2019. 1, 2, 5, 8

[76] Jinkai Zheng, Xinchen Liu, Wu Liu, Lingxiao He, Cheng-gang Yan, and Tao Mei. Gait recognition in the wild with dense 3d representations and a benchmark. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 20228–20237, 2022. 2, 3, 7, 8

[77] Haidong Zhu, Zhaocheng Zheng, and Ram Nevatia. Gait recognition using 3-d human body shape inference. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 909–918, 2023. 3, 7

[78] Zheng Zhu, Xianda Guo, Tian Yang, Junjie Huang, Jiankang Deng, Guan Huang, Dalong Du, Jiwen Lu, and Jie Zhou. Gait recognition in the wild: A benchmark. In *IEEE International Conference on Computer Vision (ICCV)*, 2021. 2, 8